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Abstract

We use a randomized experiment involving 7,029 late-paying clients of a large Colombian bank to compare the effects on loan delinquency of text messages that encourage repayment through different behavioral angles – increased attention, reciprocity, social norms, moral norms, and environmental and sustainability concerns. We find that receiving a behavioral message decreases borrowers' average likelihood to be late by 4%. The effects are more pronounced when messages leverage social norms. Heterogeneity analysis shows that our results are concentrated among late-paying borrowers with a good credit history. We also find evidence that customers who are late on unsecured loan products respond more to the messages. Our intervention provides novel evidence that behavioral messages are most effective when borrowers are marginally struggling to repay and have preferences to be on a good repayment track. In a second experiment pushing the same messages to 8,019 on-time borrowers, we find precisely estimated zero effects, suggesting that these types of messages may not be the right tool to prevent on-time borrowers from falling into loan delinquency.

JEL: G51, D91.

Keywords: Loan Delinquency, Behavioral Messages, Personal loans, Field Experiments

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1 Introduction

A non-negligible share of households around the world fails to repay their debt obligations on time. In 2020, 2% of households in the US were delinquent on their mortgage loans, and 2.5% defaulted on their credit card debt (FRED, Federal Reserve Economic Data, 2022a,b). In Colombia, 6.4% of borrowers were delinquent on their credit cards and 7% on their mortgages in the last quarter of 2020 (Transunion, 2021). Loan delinquency and, in the most extreme cases, default is associated with negative economic, financial, and social outcomes for borrowers. These include lower credit scores, worsened access to credit in the future, loss of social benefits, and worse mental health (Bos et al., 2018; Dobbie et al., 2020; de Roux, 2021; Gathergood, 2012). In the aggregate, low repayment rates may also exacerbate the financial sector's liquidity risk (Mian and Sufi, 2015). Hence, interventions that help borrowers maintain a good repayment behavior have important implications for the well-being of households and of society at large.

In recent years, a growing literature in household finance has shown that behavioral biases such as limited attention or the tendency to procrastinate can negatively affect financial decisions (Stango and Zinman, 2014; Soll et al., 2013; Fernandes et al., 2014; Campbell, 2016). Several solutions like repayment reminders and moral appeals have been tested to reduce indebtedness and default (Cadena and Schoar, 2011; Karlan et al., 2012; Bursztyn et al., 2019; Adams et al., 2021). However, identifying which intervention has the largest impact on loan repayment and the characteristics of the borrowers who respond to these interventions the most requires testing in the same context different behaviorally motivated messages and with a large and homogeneous population.

In this paper, we tackle both challenges through a randomized intervention involving a sample of 7,029 households borrowing from a large Colombian financial services provider ("the Bank" henceforth) that offers customers a suite of financial products ranging from mortgage loans to credit cards. At the onset of the study, all these borrowers were late in repaying their outstanding loans, with an average of 6 days past due. In partnership with the Bank, we designed six different messages that were randomly assigned at the individual customer level and pushed weekly via text messages. We consider a "reminder" treatment that stresses the importance of repaying on time to avoid additional costs, a "reciprocity" treatment that touches upon the trust and reciprocity between the Bank and its customers, a "moral norms" treatment that leverages the morale appeal of debt repayment, a "social norms" treatment that highlights the good repayment behavior of other bank customers, and, finally, two treatments that emphasize the ability of a financially healthy bank to make socially responsible investments. By simultaneously testing in the same context different treatments, our intervention allows us to understand the relative importance of each behavioral message.

Five weeks after the start of the intervention, we find that being exposed to any of these message streams decreases the likelihood of being late by 4% compared to a baseline likelihood of 59% in the control group. These effects are precisely estimated and consistent across different measures of loan delinquency. Only the moral and social norms messages have a negative and significant effect on the probability of being late. The strongest effect is found for the social norms message. These results indicate that nudging delinquent borrowers to repay can be particularly effective when messages highlight the social value attached to loan repayment.

Leveraging rich administrative data from the Bank and other secondary data sources, we explore potential mechanisms explaining our results by looking at heterogeneous treatment effects of borrowers' characteristics at the onset of the intervention. Borrowers with higher credit scores drive the reduction in loan delinquency. We also find that customers holding consumption loans and credit cards are more likely to respond to messages; conversely, we find no effect on those with collateralized credit (mortgages in particular), a result that aligns with Keys et al. (2016)'s study that finds little impact of information campaigns on homeowners' likelihood to refinance their mortgages. Our findings suggest that behavioral messages to improve repayment performance may be especially effective on a specific segment of the borrowers' population: delinquent borrowers that have preferences for repayment and that are of better quality within the pool of late-paying borrowers.

Yet, one may wonder how the main insights of our experiment can be broadly incorporated into strategies to prevent individuals from falling into default. A related concern is whether behavioral messages can be useful to motivate repayment behavior of borrowers at large, not only of late-paying borrowers. To answer this question we run a second randomized controlled trial testing the same set of treatment arms with 8,019 on-time paying borrowers of the Bank. The effects on this population are precisely estimated at zero, indicating that behavioral messages are not an effective strategy to prevent on-time borrowers from becoming late payers.

Taken together, the results from the two experiments suggest that interventions that provide a message that focuses on the social norms of repayment are most effective to mitigate loan delinquency when borrowers are marginally struggling to repay. On the contrary, messages do not appear to have an effect on improving the behavior of high-risk delinquent borrowers, who possibly would need a bigger "push" than a simple message – for example, financial literacy programs (Lusardi and Tufano, 2015; Kaiser et al., 2021) or better disclosure of contract terms (Bertrand and Morse, 2011). Likewise, behavioral messages do not seem the right tool to prevent on-time borrowers from falling into loan delinquency, urging more research to test what works best for this population.

Our experiment expands the frontier on behavioral interventions in consumer finance along two main dimensions: First, we test several behavioral interventions on a large, homogeneous population of borrowers by comparing key drivers of loan repayment – reminders that reduce procrastination; moral and social norms, but also new channels like borrowers' preferences for sustainable investments. Second, we employ administrative data from the Bank to study heterogeneous treatment effects based on a large set of borrower characteristics.

With this paper we contribute to the rich literature in household finance that documents how equipping borrowers with information that increases the salience of debt can have a positive impact on borrowing and repayment rates (Agarwal et al., 2015; Stango and Zinman, 2014; Soll et al., 2013; Medina, 2021; Cadena and Schoar, 2011; Karlan et al., 2012; Seira et al., 2017; Adams et al., 2021). While most of these papers focus on information provision to credit card holders, the main novelty of our experiment is that we test the effect of different behavioral messages on the repayment of a broad set of financial products. We conclude that messaging late-paying borrowers with social norms of debt repayment is the most effective tool to mitigate repayment delinquency, particularly for unsecured loans. Our paper is particularly close to Bursztyn et al. (2019)'s study of the impact of leveraging debt morale to improve repayment rates for credit cardholders. We add to their results by studying the effects of behavioral motives on credit repayment beyond the Islamic finance context, and by exploring the heterogeneous impacts of these messages based on borrowers' characteristics and type of products held.

Our paper also relates to the literature on the negative effects of bad credit scores resulting from loan delinquency in consumer credit (Bos et al., 2018; Dobbie et al., 2020). Contrary to Dobbie and Song (2020), Liberman et al. (2021) and de Roux (2021), who study potential sources of financial distress that lead to repayment default and bad credit scores, we focus on the impact of simple, cost-effective messages on reducing repayment default and mitigating the negative implications on borrowers' access to employment, health services, and future credit (Mueller and Yannelis, 2019; Bernstein, 2017).

2 Institutional Context and Experimental Design

The Bank offers customers a suite of financial products that range from mortgage loans to credit cards and consumer loans; customers may take multiple products. If borrowers are more than 30 days late on any of their loans, they are charged higher interest rates and they are reported by the Bank to the credit bureaus operating in Colombia, which proceed with the borrowers' credit score downgrading. When this happens, the Bank notifies the customer with an email that explains that they are being reported.

In collaboration with the Bank, we designed a randomized intervention to mitigate loan delinquency rates leveraging simple, short messages sent via SMS. These messages were sent to customers that were late by at least one day and in at least one product at the start date of the experiment, i.e., May 3rd, 2021. The experiment lasted three months. During these three months, the Bank agreed not to get in touch with customers to provide debt management advice or to offer promotions, a standard practice at the Bank. However, because of legislative requirements, the Bank could not avoid notifying customers if they were 30 days past due or reporting them to credit bureaus. To neutralize any potential confounding factors, the results we present in this paper refer to the first five weeks of our intervention. A timeline of the experiment can be seen in Figure 1. Clients in each treatment arm received the same behavioral message on a weekly basis until they repay all their products; no further message was pushed to them afterward.

The text messages were pushed to customers to the phone number they indicated when they enrolled with the Bank.[1] We used the same provider the Bank partners with for home-banking services. Late-paying customers were identified through administrative records, which contain socio-demographic information like income, place of residency, and credit score for each borrower. Some customers are considered by the Bank as "central nodes" for information diffusion (Banerjee et al., 2014) based on an internal algorithm for social media analysis and were therefore excluded from the study to avoid spillover effects of the treatments – e.g., these customers could have posted the messages they received on Twitter or other social media platforms. Out of the clients who were late on May 3rd, 2021, we randomly selected 7,063 and sent the first set of messages to those who were still late on May 4th (7,029 borrowers). The final sample was stratified based on the customers' credit score and a segment variable that reflects the type of lending relationship with the client. Clients were assigned to 20 strata and randomly selected into each treatment and control group. Section A in the Appendix provides details on the construction of the strata.

2.1 Experimental Treatments

The experimental design is shown in Figure 2. Each treatment arm is associated with a different stream of messages that was pushed to 1,009 clients. In the control group, no message was pushed. Each experimental subject was uniquely assigned to either receive one of the treatments or to be in the control group. In this section, we present the exact wording

[1]There may be cases in which clients' numbers changed since enrollment. The Bank regularly verifies clients' contact details to ascertain that clients can be successfully reached.

of each message (translated from Spanish) and discuss the behavioral motivation behind it.

S1 (Reminder of financial implications of default): Clients assigned to S1 received the following message: *"The Bank reminds you that people who pay their loans on time take care of their money by not paying interest on arrears. Take care of your money by paying your financial products on time"*. This treatment arm speaks to the literature on financial sophistication and borrowing behavior (Lusardi and Tufano, 2015; Bertrand and Morse, 2011) and aims at testing the role of limited attention in loan repayment (Stango and Zinman, 2014). By increasing the salience of the economic consequences of loan delinquency, borrowers should be moved to reduce defaults.

S2 (Reciprocity): Clients randomly assigned to S2 received the following message: *"At the Bank, we trusted you by giving you the money you needed. In the same way, we trust that your financial commitments will be paid on time"*. This message leverages the obligation/reciprocity relationship between the customer and the Bank. It could make borrowers feel an obligation towards the institution, which can increase their repayment efforts (Karlan et al., 2012; Charness and Dufwenberg, 2006).

S3 (Moral obligation of debt repayment): Clients randomly assigned to S3 received the following message: *"Nothing generates more peace of mind than a duty accomplished. By paying your financial products on time, you meet your commitments and live peacefully."* This message leverages the morality of *not* defaulting on one's debt, which in turn may enhance loan repayment (Guiso et al., 2013; Bursztyn et al., 2019).

S4 (Social norms): We administered a fourth stream of messages that leverage social norms of repayment. The text message reads as follows *"Did you know that 8 out of 10 Colombians pay their loans on time? Be part of this group and keep up to date with your financial products."* This message appeals to two aspects of social norms: first, to the descriptive aspect of norms with salience to Bank clients' pool. Second, there is a clear reference to the minority vs. majority norm, whereby borrowers are encouraged to be part of a majority that pays on time. While these types of messages are frequently used to encourage household savings (Beshears et al., 2015; Kast et al., 2018; Dur et al., 2021), tax compliance (Hallsworth et al., 2017; De Neve et al., 2021), and payment of TV licensing (Fellner et al., 2013), they have rarely been used to reduce repayment delinquency. Whether social norms positively affect repayment rates remains an empirical question that largely depends on the group (minority vs. majority) our experimental subjects identify with.[2]

[2]Individuals' preferences, choices, and self-image are affected by their perception of the behavior of others. This fact should also apply to our bank clients. For example, knowing that the majority is paying on time should affect repayment rates, similar to how energy or water users respond to such social comparisons (Allcott, 2011). Related to this, Gathergood (2012) reports that the psychological costs of indebtedness are lower when bankruptcy rates are higher among the borrower's peers. Therefore, a perception of higher

S5 and S6 (Socially Responsible Investments Concerns): We included two streams of behavioral messages that leverage borrowers' concerns for the Socially Responsible Investments (SRI) carried out by the Bank. Clients randomly assigned to S5 and S6 received the following message: *"With the payment of your financial products, the Bank invests in the country with projects that generate social and environmental benefits, such as access to decent housing and the fight against climate change. With your payment on time, you make a difference and support this transformation."*. Clients in S6 receive an additional portion of the message: *"Learn more about our investment here (weblink to the Environmental, Social and Governance (ESG) page of the Bank)"*. So far, most of the literature on SRI has focused on how investors' preferences for ESG criteria affect investments (Pedersen et al., 2020; Krueger et al., 2020). We know little about how banks can leverage *debtors'* preferences for SRI (and, more generally, ESG) to enhance repayment rates. The hypothesis behind S5 and S6 is that by leveraging borrowers' concerns for a specific set of public goods (i.e., the fight against climate change), the Bank makes borrowers feel more compelled to repay. The additional inclusion of a web link that allows borrowers' to verify the type of investments the Bank engages in, enables us to test whether a simple message on the Bank's SRI is sufficient, or if this type of message requires that the financial institution provides detailed information about the investment.

All messages we pushed in our experiment also gave the clients the possibility to reach out to the Bank by including the following sentence: "Do you want to communicate with us? Contact us at [number]".

3 Conceptual Framework

Our experiment allows us to answer three key questions in the household finance literature: first, whether providing delinquent borrowers with behaviorally-motivated messages improves repayment behavior; second, which message is the most effective in the same context; third, which borrowers are more sensitive to behavioral messages. Several types of interventions, ranging from text reminders to messages with moral considerations, have shown positive effects on borrowing and repayment behavior (Agarwal et al., 2015; Stango and Zinman, 2014; Soll et al., 2013; Cadena and Schoar, 2011; Bursztyn et al., 2019; Medina, 2021). Yet, the underlying mechanisms of their impact remain largely unexplored.

The behavioral literature has identified three conditions that ensure that behaviorally motivated messages (see Damgaard et al., 2020 for a review) can be effective. First,

repayment rates in the social group should increase the psychological costs of delinquency and push the client to increase his effort to pay on time.

individuals must have the potential to improve their behavior (as shown by Allcott, 2011). Second, they must be motivated to improve their behavior (Gravert and Kurz, 2021). Finally, their decisions and actions must be precisely constrained by the behavioral barrier the nudges aim at targeting and mitigating (Dinkelman and Martínez A, 2014).

In the context of debt repayment, these predictions imply that borrowers who have money to repay and whose credit score can still be "redeemed" should respond to messages encouraging repayment the most. If borrowers believe that, irrespective of their effort to repay, they will not have access to credit in the future, messages will hardly have an effect. At the same time, behavioral messages will have a greater impact on borrowers with higher preferences for repayment. This is the case if they obtain utility from being up to date for reasons unrelated to the direct economic consequences of being late, like the report to credit bureaus or overdue fees. For example, customers could obtain utility from being on time if they see a social or moral value in this or if being late negatively affects their self-image. Finally, another dimension that could matter for messages to have an effect is whether or not the customer is delinquent. Borrowers who are on time are not directly constrained by the specific behavioral barriers targeted by the messages, and hence they should be less sensitive to our text treatments.

We test the above predictions with rich, granular data on borrowers' characteristics. Heterogeneous treatment effects allow us to assess the impact of behavioral messages on low-risk versus high-risk delinquent borrowers. We also investigate heterogeneous effects along the gender, age, and product dimensions. In addition, comparing the results from our main experiment with those of a second experiment in which we push the same set of text messages to on-time borrowers provides us with insights on whether behavioral messages improve the repayment behavior of all borrowers or just that of delinquent ones.

4 Data and Empirical Approach

4.1 Summary Statistics

The data we use in the analysis mainly come from administrative records held by the Bank. For each credit product held by a borrower in our experimental sample, the Bank has shared daily information on the number of days past due.[3] Importantly, if a borrower repays during the intervention, this information allows us to know the exact day the payment was made. We also have socio-demographic information, including the gender of the borrower, monthly income, education, and occupation at the start of the intervention. Financial information like

[3]If the borrower's repayments for a specific financial product are up to date, this variable is equal to 0.

the total amount of outstanding debt and assets, as well as a credit score, are also available. We also have measures of customers' engagement with the Bank (e.g., whether and when the client has reached out to the Bank's customer care).

Table 1 shows summary statistics for the sample of 7,029 borrowers included in our study, separated between control and treatment groups. Half of the customers in our sample are women; they are on average 42 years old and with a monthly household income of around 4,200 thousand Colombian Pesos (approximately $1,124 USD).[4] Borrowers in our sample are fairly well educated, with almost 90% of them having completed higher education; the largest share of borrowers are employed and residing in the Central region of Colombia. Finally, borrowers are on average between 5 to 6 days late with their loan payment at the onset of the study.[5] The table also presents the p-value of a test of joint significance of the coefficients from a regression where the left-hand variable is the control listed in the first column and the right-hand variables are dummies for treatment assignment. The p-values reported in the table show that the control and the treatment groups are well balanced across all socio-demographic and financial characteristics, reassuring us that the randomization worked well.

4.2 Econometric Specification

We start by studying the effect on loan repayment of receiving any behavioral message for late borrowers. Individuals who completed their loan repayment during the intervention are dropped out of the estimation sample in the week of their final repayment. We estimate the following regression in a balanced panel at the individual-week level:

$$y_{iw} = \beta_0 + \beta_1 T_i + z_i + c_w + \epsilon_{iw} \tag{1}$$

where y_{iw} is the probability that client i is late in week w in at least one product and T_i is a dummy that equals one if the subject is randomly assigned to receive any of the message streams. z_i is a vector of strata fixed effects, c_w denotes week fixed effects, and ϵ_{iw} is the error term. To account for individual unobserved heterogeneity, we also estimate equation (1) including in the vector z_i a set of individual-level predetermined characteristic that we select with a double LASSO procedure (Belloni et al., 2014).[6] Standard errors are clustered

[4]Throughout the paper we use an exchange rate of 3,735 Colombian Pesos per US Dollar, which was the average exchange rate in May 2021, the month of our intervention.

[5]If the borrower's repayments for a specific financial product are up to date, this variable is equal to 0.

[6]We let the LASSO procedure select the relevant characteristics from the following list: income, age, value of outstanding debt, occupation and region dummies, and dummies for whether the borrower is a women, has a couple, or has children. Table 1 shows that some characteristics have missing values. We recode the missing values to 0 and define dummies that indicate if the corresponding covariate is missing. We include in the LASSO selection list both the recoded variable and the corresponding missing dummy and include

at the individual level. Our main coefficient of interest is β_1, the Intent-to-Treat coefficient.[7]

In a second specification, we look at the impact of each individual treatment by estimating the following equation:

$$y_{iw} = \beta_0 + \sum_{j=1}^{6} \beta_j T_{ij} + z_i + c_w + \epsilon_{iw} \tag{2}$$

where T_{ij} is a vector of dummies denoting random assignment, at the individual level, to any of the six message streams S_j discussed in Section 2.1.Equation (2) allows us to identify which message stream is the most effective in improving repayment rates. We estimate both equation (1) and equation (2) with administrative data from the Bank.

5 Results

5.1 The Effect of Receiving Any Message

We study treatment effects by first examining the impact of receiving any type of message. Results from estimating equation (1) are shown in Panel of A of Table 2. Column (1) shows the results including as controls only strata fixed effects. Compared to the control group, receiving any message decreases the probability of a borrower being late by 2.3 percentage points – a decrease of 4% relative to a delinquency rate of 59% in the control group. Column (2) shows that this result is robust to the inclusion of week fixed effects and column (3) shows that it is robust to the inclusion of individual-level characteristics chosen with LASSO. The estimated coefficient is fairly stable across specifications suggesting that the randomization was successful. The results from this table provide strong evidence that behavioral messages are effective at reducing loan delinquency.

To corroborate the results shown in Table 2, we estimate treatment effects on the intensive margin of loan delinquency, measured as the maximum number of days borrowers are late across all their products at the end of the week. Results are shown in Panel A of Appendix Table A1. On average, borrowers in the control group are 6 days late in repaying their loans. Receiving a message reduces the number of days the debt is past due by almost

both variables in the final regression if the characteristic is selected by the LASSO procedure.

[7] This is an intent-to-treat effect since we cannot guarantee that the borrowers actually read the text message. At the end of the intervention, we invited by email all the clients in our experiment to participate in a short survey. We obtained 234 answers or a response rate of 3.3%. 70% of those who answered recall receiving a message from the Bank related to the importance of paying on time. This suggests that an important fraction of our customers were indeed reading the text messages of the intervention. Note also that non-compliance works against finding an effect of messages. In other words, with perfect compliance, that is if all the borrowers were to read the messages, we would expect an effect of messages on repayment that is larger than the one reported in this section.

9%. This result holds both in significance and in magnitude in regressions with strata fixed effects (column 1), strata and week fixed effects (column 2), strata, week fixed effects, and individual-level controls (column 3), which adds to the evidence that our behavioral messages positively impact repayment behavior.

5.2 The Effect of Individual Behavioral Messages

We dig deeper into our main result and study treatment effects for each individual message stream, by estimating equation (2). Results are shown in Panel B of Table 2. We observe that treatment effects are particularly pronounced when borrowers are exposed to messages that leverage social norms for repayment: receiving a message that emphasizes social norms reduces the probability a borrower is late by around 4.5 percentage points (or about 7.7% relative to the mean delinquency rate of the control group). Appendix Table A2 presents p-values of tests that compare the coefficients of Column (3) in Panel B of Table 2. The table shows that some of the effects of the individual messages can be distinguished from each other. In particular, the effect of the social norms message can be distinguished at the 10% level from the contract reminder and the social responsibility messages. The moral norms message reduces the delinquency rate by close to 2.7 percentage points (or about 4.6% relative to the control group mean). The messages that emphasize reciprocity between the borrower and the Bank, and Environmental, Social, and Governance (ESG) investments do not have a robust effect on borrowers' delinquency. Finally, we note that the treatment effect of the contract reminders are close to zero and not statistically significant.

Taken together, results from Table 2 indicate that messages appealing to social and moral norms work well to reduce loan delinquency. Importantly, these findings provide novel evidence in the context of personal loans on the effectiveness of messages that appeal to social comparisons. We also provide novel evidence that messages emphasizing the socially responsible investments carried out by the Bank, and that also give the borrower the possibility to verify these investments through a web link, do not have strong effects on repayment rates.

5.3 Robustness Checks

This section discusses several checks we performed to ensure the robustness of our main results. First, one feature of our experimental design is that the first text message was pushed to all treated borrowers (6,026 out of 7,029) on the exact same day (May 4th, 2021). This means that, at the start of our intervention, borrowers were late to a different extent – 50% of the borrowers at the start of the intervention were at least 4 days late, and 5% were at least 17 days late. Even if the number of days past due is balanced across treatment and control groups (see Table 1), one may wonder whether our results may be affected by the extent of borrowers' lateness – and particularly by late-paying borrowers who at the start of the intervention found themselves relatively closer to the 30-days cutoff, after which the Bank has the obligation to report defaulting customers to credit bureaus.

To ensure that our results are robust to this concern, we estimate equations (1) and (2) controlling for the number of days past due at the start of the intervention in addition to the usual controls. For clients with multiple products, we average across products to obtain the number of days past due at the beginning of the intervention. Results are reported in columns (1), (2) and (3) of Appendix Table A3. Treatment effects of receiving any message, as well as of individual messages, remain practically unchanged.

A second concern is that our effects could be confounded by regional time-varying characteristics (e.g., some regions of Colombia could have been differently hit by the Covid-19 pandemic, thus affecting borrowers' ability to repay their loans). We run another robustness check including region$\times$week fixed effects; results are shown in column (4) of Appendix Table A3. Again, our main coefficients of interest remain very similar to those reported in Table 2.

Finally, we test whether behavioral messages also reduce delinquency if we take together the complete five-weeks time period. That is, we estimate equations (1) and (2) in the cross-section of late borrowers and use as outcome the maximum number of days past due (across products) in the five weeks after the start of the intervention. Results are reported in Appendix Table A4. Column (2) in Panel A shows that receiving any message reduces the maximum number of days past due by 0.97 days (or 7.5% relative to the mean of the control group). Individual messages also have an effect on reducing the maximum number of days past due. As before, the largest negative impact corresponds to the social norms message that reduces the maximum number of days past due in the month by 1.67 days (or 13% relative to the mean of the control group).

The results of Sections 5.1 to 5.3 show that behavioral messages improve repayment behavior. In the next section, we explore whether these effects are more pronounced for certain population groups.

5.4 Heterogeneity: Borrower Characteristics and Trust

Granular administrative data from the Bank allow us to study the heterogeneous effects of messages on loan repayment based on borrowers' characteristics. We estimate the following regression equation:

$$y_{iw} = \beta_0 + \beta_1 T_i + \beta_2 X_i + \beta_3 T_i \times X_i + c_w + z_i + \epsilon_i \tag{3}$$

where T_i is a dummy equal to one if borrower i received any of the messages, X_i is a dummy indicating whether borrower i has a particular pre-specified characteristic, c_w denotes week fixed effects, and z_i denote individual controls that include strata fixed effects and individual characteristics selected using the double LASSO procedure. β_3 is our coefficient of interest; it captures how the effect of the treatment differs for individuals with different values of X_i. We look at heterogeneous treatment effects by pooling the treatments but we also consider a second specification where we estimate heterogeneous treatment effects of each message separately.

We consider three sources of heterogeneity leveraging borrowers' socio-economic status from the Bank's administrative data: credit score, gender, and age. We define X_i as a dummy equal to 1 if borrower i had a credit score above the median at the beginning of the intervention.[8] Second, we define X_i as a dummy equal to 1 if borrower i is a woman. Third, X_i is a dummy equal to 1 if borrower i's age is above the median age in the sample. Finally, we consider whether the effect of behavioral messages depends on the level of trust in Banks. For this test, we define X_i as a dummy equal to 1 if borrower i lives in a department of Colombia with high trust in banks. We gather this measure of trust from the 2018 wave of the World Value Survey, which asks respondents to state how much they trust different organizations, including banks, on a scale of 1 to 4. For each of the 32 departments of Colombia in the survey, we calculate the average trust for banks and define X_i as a dummy equal to one if borrower i's place of residency is in a department with an average level of trust above the median.[9]

Table 3 reports the results of the heterogeneity exercises. Panel A presents heterogeneity results for the effect of receiving any message. Column (1) shows that the negative effect on the probability of being late is entirely driven by individuals with credit scores above the median. Columns (2) and (3) of Panel A show that in the aggregate there are no heterogeneous effects depending on the gender or the age of the borrower since the coefficients of the interaction with X_i are precisely estimated zeros. Column (4) of Panel B shows that the effect of receiving any message is more pronounced in places with high trust in banks; the point estimate of the interaction is -0.0181 suggesting that the effect doubles in places with high trust, although the estimate is imprecise.

[8] Recall that the credit score is calculated by the Bank with a machine learning algorithm using the administrative data.

[9] The 32 departments of Colombia are divided in the six regions listed in Table 1.

The heterogeneity results for the individual messages are reported in Panel B of Table 3. Regarding the credit score, as with the aggregate effect, the effect of the individual messages is mostly driven by individuals with high credit scores. Regarding the gender and the age of the borrowers, and although there are no heterogeneous effects in the aggregate along these dimensions, there is some heterogeneity for the individual messages. For example, the table shows that the contract reminder has a an effect on women (although not significant) and not on men, while the reciprocity treatment reduces delinquency for men and not for women. Young borrowers seem to be more affected than older borrowers by the contract reminder and the reciprocity treatments since the coefficients of the interactions are positive and large (although imprecise). These results are interesting in contrast to other results in the literature. For example, Bursztyn et al. (2019) finds larger effects in the repayment of credit cards of messages with moral cues with borrowers with high ex-ante credit risk but no heterogeneous effects along the gender, age, or religion dimensions. Consistent with our findings Cadena and Schoar (2011) find stronger effects of reminders on repayment for young customers.

5.5 Heterogeneity by credit products

We also ask if there are heterogeneous treatment effects based on product type. This question is important since it can tell us whether behavioral messages are useful to reduce delinquency of uncollateralized credit, which is riskier for the Bank. We consider the following categories of products: credit cards and consumption loans which are uncollateralized, and collateralized loans like mortgages.[10]

We estimate equations (1) and (2) separately for each credit product and report the results in Table 4. The sample in each column consists of borrowers that had *at least* the financial product listed in the column header. As in previous tables, Panel A shows the effect of receiving any behavioral message while Panel B shows the effect of individual messages. The results show that the effect of behavioral messages is concentrated among borrowers that hold at least a credit card or a consumption loan. There are no effects on borrowers with mortgages. This is true if we consider the effect of receiving any message (Panel A) or the effect of individual messages (Panel B). These results suggest that behavioral messages can be particularly effective when customers hold unsecured financial products. At the same time, these findings expand Bursztyn et al. (2019)'s analysis by showing that messages are not

[10]These products also differ in other important dimensions. In our sample, the average interest rate is 24.8 for credit cards, 25.7 for consumption loans, and 13.5 for mortgages. Consumption loans have an average term of 4.25 years while the average term is 18.3 years for mortgages. In our main sample, there are 3 clients with a microcredit product, 60 clients with leasing, and 327 with revolving credit but we exclude them from this heterogeneity analysis given their small number.

only effective for customers holding credit cards, but also consumption loans and, potentially more broadly, uncollateralized credit products.

5.6 An experiment with on-time borrowers

So far, our main results show that the most effective message leverages borrowers' desire to comply with social norms. At the same time, heterogeneous treatment effects show that the impact of messages on loan repayment is particularly pronounced when borrowers have a relatively high credit score despite being delinquent. Taken together, these findings suggest that behavioral messages are effective tools to improve repayment behavior only when they target a specific segment of the borrowers' population: borrowers that have preferences for repayment and that are of better quality within the pool of delinquent borrowers, and hence have scope to improve their repayment behavior.

But do behavioral messages improve repayment behavior at large – that is, are they also effective to keep non-delinquent borrowers on time? Answering this question is key to understand which segment of the borrowers' population should be targeted with messages to mitigate loan delinquency, and whether other interventions may be more effective for this group. To assess this possibility, we run a second randomized controlled trial where we administer the same set of treatments to approximately 8,000 borrowers of the Bank that at the onset of the study were on time with their repayments. Appendix Figure A1 shows the timeline of the intervention and Appendix Figure A2 shows the experimental design. We included an additional treatment group to which we send a message stream that congratulates the borrower for being on time. We estimate equations (1) and (2) on this group and report the results in Table 5. Panel A shows no effect of receiving any behavioral message on the probability of loan delinquency. The coefficient of each specification is precisely estimated at zero. Panel B considers the effect of individual messages and shows that none of them has any effect on on-time borrowers. Results from this second experiment corroborate our hypothesis that interventions to improve repayments are effective tools when borrowers are marginally struggling to repay. On the contrary, behavioral messages do not appear to be equally effective in improving the behavior of very delinquent borrowers, who possibly would need a bigger "push", for example through financial literacy training (Bertrand and Morse, 2011; Lusardi and Tufano, 2015), than a simple message. Similarly, they do not seem the right tool to prevent on-time borrowers from falling into loan delinquency.

5.7 Gains from the Intervention

In this final section, we provide a back-of-the-envelope calculation of the additional benefits for the Bank if it were to send the social norms message to the pool of late borrowers in a given month. We focus on the increase in profits that result from the time value of money. If a customer pays on time then the Bank can use that money to invest, for example by lending the proceeds to another customer. On the other hand, bank customers can gain from the intervention thanks to the reduction in late payment fees and additional interest rates.

Regarding the reduction of costs for the bank from loan delinquency, recall that the social norms message leads to a reduction of 1.67 days past-due on average per month.[11] From Table 1, the yearly average interest rate (across products) is 22% or approximately $22/365\% = 0.06\%$ per-day. Furthermore, from the Bank administrative data, we can recover the average amount our late borrowers had to pay at the beginning of the intervention and on which they were late. This number is around 652 thousand Colombian Pesos. Therefore the amount of money saved per month by the Bank on each borrower that receives the social norms message is around 653 pesos ($= 1.67 \times 652,000 \times 0.0006$). On May 4th, 2021 we selected our experimental sample of 7,000 late borrowers from a pool of late borrowers of around 120,000. Therefore, the total benefit of sending the social norms message to this group would have been $120,000 \times 653 = 78,360$ thousand COP (approximately 20,980 USD). This figure is considerable and corresponds to the benefits of applying the intervention to the population of late clients in a given month. This can be repeated month by month leading to even higher profits.

6 Conclusions

The notion that individuals respond to financial, social, and moral motives is now accepted for a vast array of domains in which individuals interact in markets, communities, and with the state. In the financial sector and the credit market, in particular, this should be no exception. We run a large-scale randomized controlled trial with a large Colombian bank to test the effectiveness of behaviorally inspired messages to improve the repayment behavior of delinquent borrowers. We implement six streams of text messages that are randomly administered at the individual level to a sample of 7,029 customers of our partner bank.

Our setting allows us to push the frontier on behavioral interventions in consumer finance in two important ways: First, we test several behavioral interventions against each other on a large, homogeneous population of borrowers. This allows us to compare key drivers of

[11]See results obtained in the cross-section of borrowers reported in Appendix Table A4 and the discussion in Section 5.3.

loan repayment – reminders, debt morale, and social norms – and also compare their effect to that of potential new channels like borrowers' preferences for sustainable investments. These types of behavioral motives have been extensively studied in other domains like in the environmental economics literature, but less so studied in consumer finance. Second, we employ a rich set of administrative data from the Bank that allow us to observe repayment rates and borrowers' characteristics, including their credit score, throughout the experiment. This allows us to study heterogeneous treatment effects based on observables.

We find positive and substantial effects of receiving a behaviorally motivated message on repayment behavior (+4%); much of these effects are driven by motivations leveraged by social norms. Our results are precisely estimated and robust to time fixed-effects and individual-level controls. Heterogeneity analysis indicates that our results are concentrated among late borrowers with a good credit history and among uncollateralized credit products. A second experiment with on-time borrowers finds no effects from these messages.

We conclude that behavioral messages to improve repayment performance may be especially effective on marginally delinquent borrowers – that is, borrowers that have preferences for repayment and that are of better quality within the pool of delinquent borrowers, and hence see scope to improve their repayment behavior. On the contrary, behavioral messages do not appear to have an effect on improving the behavior of very delinquent borrowers, who possibly would need a bigger "push" than a simple message or that are under severe financial constraints. Likewise, these types of messages do not seem the right tool to help sustain on-time borrowers out of loan delinquency, urging more research to test other types of messages for this segment of the borrowing population.

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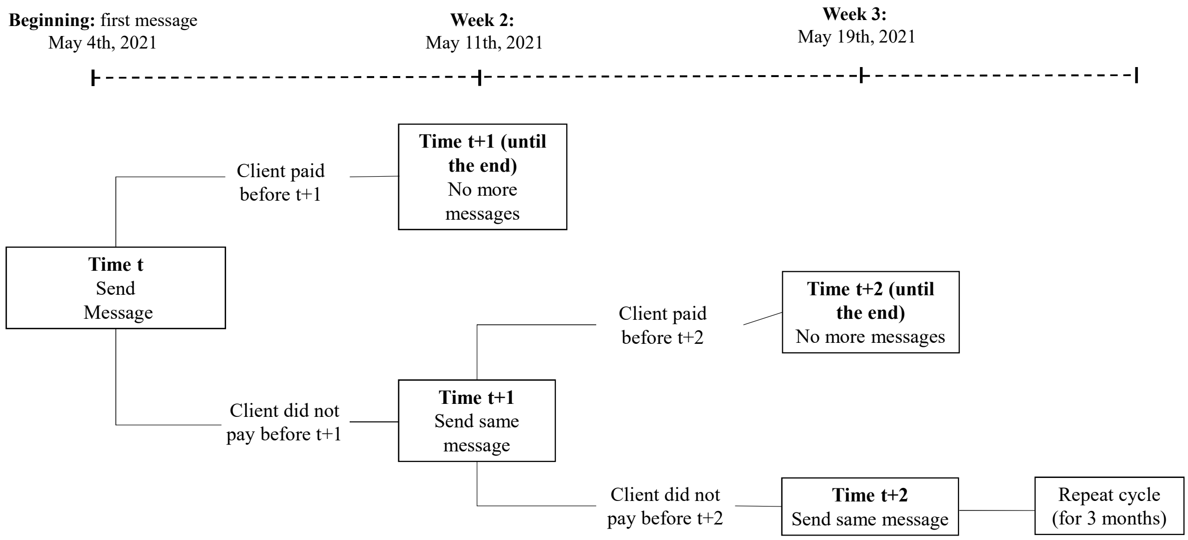
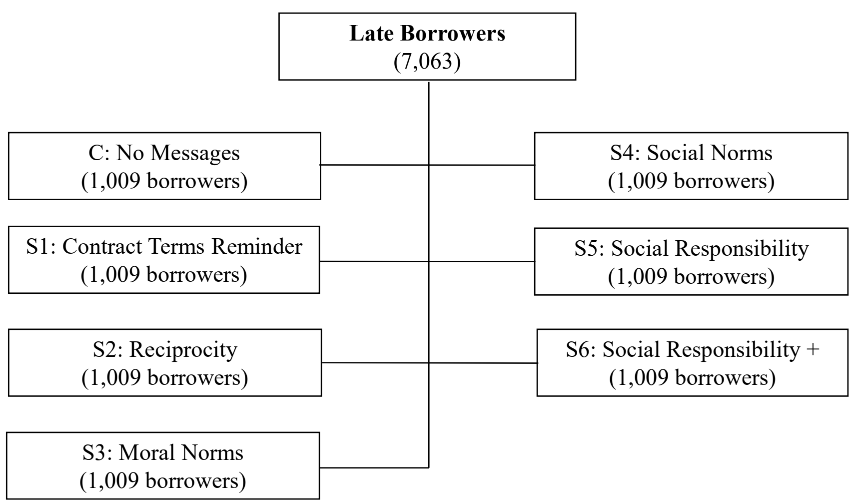
Figure 1: Intervention Timeline



Notes: The figure shows the timeline of our intervention with late-paying borrowers. The first text message was pushed to all treated borrowers in the experiment on May 4th, 2021. Borrowers received messages on a weekly basis for 3 months until they fully repaid.

Figure 2: RCT design



Notes: The figure shows the design of our intervention. We selected 7,029 late-paying clients and randomly allocated them with equal probability to either the control group or to one of six different message streams.

Table 1: Balance Checks – Late-paying Borrowers

	Control group			Treatment (pooled)			T-test
	N	Mean	Sd	N	Mean	Sd	(p-value)
Women	1,003	0.50	0.50	6,026	0.51	0.50	0.61
Age	1,003	42.35	13.00	6,022	41.91	13.22	0.32
Couple	856	0.47	0.50	5,119	0.49	0.50	0.45
# of children	1,003	0.46	0.99	6,025	0.47	1.00	0.82
Share of wallet	848	69.49	29.89	4,982	69.30	30.72	0.87
Monthly income	1,003	4,388	6,513	6,026	4,165	5,907	0.28
Debt size	1,003	29,089	43,174	6,026	30,451	48,524	0.40
Credit Score	1,003	0.69	0.22	6,026	0.68	0.22	0.91
Basic education or less	377	0.10	0.30	2,230	0.10	0.30	0.98
Secondary education	377	0.89	0.32	2,230	0.88	0.32	0.64
Higher education	377	0.01	0.10	2,230	0.02	0.14	0.24
Ocup.: Employed	950	0.83	0.38	5,722	0.83	0.38	0.89
Ocup.: Retired	950	0.07	0.25	5,722	0.07	0.25	0.76
Ocup.: Self-employed	950	0.07	0.26	5,722	0.07	0.25	0.70
Ocup.: Student	950	0.03	0.16	5,722	0.03	0.18	0.21
Ocup.: Unemployed	950	0.01	0.08	5,722	0.01	0.08	0.96
Region Amazonia (South)	970	0.01	0.08	5,832	0.01	0.10	0.45
Region Andina (Center)	970	0.65	0.48	5,832	0.64	0.48	0.51
Region Caribe (North)	970	0.13	0.34	5,832	0.14	0.35	0.51
Region Pacifico (West)	970	0.17	0.37	5,832	0.18	0.38	0.45
Region Orinoquia (East)	970	0.04	0.18	5,832	0.03	0.16	0.20
Region Outside	970	0.01	0.10	5,832	0.01	0.09	0.51
Days past-due	1003	5.78	5.46	6,026	5.80	5.69	0.89
Annual Interest Rate (%)	979	21.78	9.13	5,867	22.14	9.28	0.26
Maturity (months)	979	107.38	79.68	5,867	109.05	82.29	0.56

Notes: This table displays summary statistics of different borrower characteristics, separated between borrowers in the control group and borrowers in any of the treatment arms. N is the number of observations for which the variable is available. Couple is a dummy equal to one for borrowers with a couple. Share of wallet is the fraction of the debt that the Bank holds relative to the debt of the borrower from other banks (this information comes from credit bureaus). Monthly income and debt size are in thousands of Colombian pesos. Primary education or less, secondary education, and higher education are dummies for the corresponding educational attainment level. The occupation variables are dummies for the corresponding occupation level. The region variables are region dummies for the corresponding region of Colombia. To obtain days past due, annual interest rate, and maturity we average across all the loan products of each borrower.

Table 2: The Effect of Behavioral Messages

	Late in Week		
	A. Pooled Treatments		
	(1)	(2)	(3)
Any message	-0.0227**	-0.0228**	-0.0220**
	(0.0112)	(0.0112)	(0.0112)
Outcome mean (control)	0.593	0.593	0.593
Observations	34,781	34,781	34,781
	B. Separate Treatments		
Contract Reminder	-0.0159	-0.0159	-0.0148
	(0.0146)	(0.0146)	(0.0145)
Reciprocity	-0.0211	-0.0212	-0.0209
	(0.0145)	(0.0145)	(0.0144)
Moral Norms	-0.0252*	-0.0251*	-0.0247*
	(0.0145)	(0.0145)	(0.0144)
Social Norms	-0.0388***	-0.0388***	-0.0398***
	(0.0146)	(0.0146)	(0.0145)
Social Responsibility	-0.0135	-0.0137	-0.0118
	(0.0146)	(0.0146)	(0.0145)
Social Responsibility + Link	-0.0217	-0.0217	-0.0204
	(0.0146)	(0.0146)	(0.0146)
Outcome mean (control)	0.593	0.593	0.593
Observations	34,781	34,781	34,781
Stratum FE	Yes	Yes	Yes
Week FE	No	Yes	Yes
Controls (LASSO)	No	No	Yes

Notes: This table shows treatment effects of behavioral messages in a sample of 7,029 late borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The dependent variable is a dummy equal to one if the borrower is late on any product in the week. In Panel A, the variable of interest is a dummy equal to one if the borrower was assigned to receive any of the message streams. In Panel B, the outcomes of interest are dummies indicating the message stream to which the borrower was assigned. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. In column (3), we use PDS Lasso to select covariates (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table 3: Heterogeneous Effects, Borrower Characteristics and Trust

	Late in Week			
	A. Pooled Treatments			
	X_i: High Score (1)	X_i: Female (2)	X_i: Age > median (3)	X_i: High Trust (4)
Any Message	-0.00346	-0.024	-0.0278*	-0.0182
	(0.0160)	(0.0152)	(0.0162)	(0.0148)
Any Message $\times X_i$	-0.0371*	0.00381	0.0109	-0.0169
	(0.0223)	(0.0223)	(0.0224)	(0.0235)
Outcome mean (control)	0.593	0.593	0.593	0.591
Observations	34,781	34,781	34,781	33,007
	B. Individual Treatments			
Contract Reminder	0.0106	0.00934	-0.0329	-0.0106
	(0.0207)	(0.0203)	(0.0210)	(0.0193)
Contract Reminder $\times X_i$	-0.0508*	-0.0464	0.0344	-0.018
	(0.0290)	(0.0290)	(0.0291)	(0.0305)
Reciprocity	0.00108	-0.0430**	-0.0386*	-0.011
	(0.0207)	(0.0200)	(0.0211)	(0.0189)
Reciprocity $\times X_i$	-0.0438	0.0443	0.0331	-0.034
	(0.0288)	(0.0288)	(0.0289)	(0.0306)
Moral Norms	-0.000558	-0.0326	-0.0117	-0.0228
	(0.0207)	(0.0199)	(0.0206)	(0.0194)
Moral Norms $\times X_i$	-0.0482*	0.0159	-0.0249	-0.0138
	(0.0289)	(0.0289)	(0.0289)	(0.0303)
Social Norms	-0.0171	-0.025	-0.0515**	-0.0423**
	(0.0206)	(0.0198)	(0.0213)	(0.0195)
Social Norms $\times X_i$	-0.0452	-0.0291	0.0226	-0.0088
	(0.0289)	(0.0289)	(0.0290)	(0.0304)
Social Responsibility	-0.00175	-0.00646	-0.0166	-0.00779
	(0.0207)	(0.0200)	(0.0207)	(0.0190)
Social Responsibility $\times X_i$	-0.0197	-0.0103	0.00904	-0.00953
	(0.0290)	(0.0290)	(0.0290)	(0.0306)
Social Responsibility (Link)	-0.0137	-0.0446**	-0.0155	-0.0158
	(0.0210)	(0.0203)	(0.0211)	(0.0194)
Social Responsibility (Link) $\times X_i$	-0.0139	0.0481*	-0.00984	-0.0155
	(0.0292)	(0.0292)	(0.0293)	(0.0308)
Outcome mean (control)	0.593	0.593	0.593	0.591
Observations	34,781	34,781	34,781	33,007

Notes: This table shows heterogeneous effects of behavioral messages according to predetermined characteristics at the beginning of the intervention, in a sample of 7,029 late borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The dependent variable is a dummy equal to one if the borrower is late on any product in the week. The heterogeneity variable is a dummy denoted by X_i. In column (1), X_i is a dummy equal to one if the credit score is above the median in the sample of borrowers. In column (2), X_i is a dummy for women, and in column (3) a dummy for borrowers with age above the median. In column (4), X_i is a dummy for borrowers living in a department where average trust in banks is above the median trust across departments (which we measure using the World Values Survey of 2018). Panel A shows heterogeneous effects for the effect of receiving any message while Panel B shows estimates for each individual message. All columns include stratum fixed effects (defined by quintiles of the credit score interacted with the Bank segment), week fixed effects, and individual characteristics selected with a double Lasso procedure (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table 4: Heterogeneous Effects, Credit Product

	Late in Week		
	A. Pooled Treatments		
	Credit Card	Consump. Loan	Mortgage
	(1)	(2)	(3)
Any Message	-0.0707***	-0.0329***	-0.00504
	(0.0255)	(0.0127)	(0.0192)
Outcome mean (control)	0.695	0.672	0.482
Observations	7,280	20,896	12,944
	B. Individual Treatments		
Contract Reminder	-0.0756**	-0.023	0.00617
	(0.0336)	(0.0166)	(0.0244)
Reciprocity	-0.0657**	-0.0365**	-0.0154
	(0.0330)	(0.0165)	(0.0251)
Moral Norms	-0.0968***	-0.0506***	0.0105
	(0.0330)	(0.0164)	(0.0251)
Social Norms	-0.0956***	-0.0493***	-0.0116
	(0.0325)	(0.0166)	(0.0244)
Social Responsibility	-0.0542*	-0.0233	0.00899
	(0.0319)	(0.0168)	(0.0250)
Social Responsibility (Link)	-0.0603*	-0.0227	-0.0246
	(0.0336)	(0.0165)	(0.0255)
Outcome mean (control)	0.695	0.672	0.482
Observations	7,280	20,896	12,944
Borrowers with product	1,499	4,244	2,602
Stratum FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Controls (LASSO)	Yes	Yes	Yes

Notes: This table shows heterogeneous effects of behavioral messages according to the credit product, in a sample of 7,029 late borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The individuals included in the sample are those that hold at least one product of the product type listed in the column header. The dependent variable is a dummy equal to one if the borrower is late on any product in the week. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. Individual-level controls are selected using PDS Lasso (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table 5: The Effect of Nudges, On-Time Borrowers

	Late in Week		
	A. Pooled Treatments		
	(1)	(2)	(3)
Any message	-0.00243	-0.00236	-0.0028
	(0.00736)	(0.00735)	(0.00735)
Outcome mean (control)	0.235	0.235	0.235
Observations	39,548	39,548	39,548
	B. Separate Treatments		
Contract Reminder	-0.00982	-0.00940	-0.00971
	(0.00964)	(0.00963)	(0.00963)
Reciprocity	-0.0117	-0.0117	-0.0133
	(0.00971)	(0.00970)	(0.00966)
Moral Norms	-0.0121	-0.0123	-0.0119
	(0.00964)	(0.00963)	(0.00961)
Social Norms	0.00504	0.00491	0.00506
	(0.00996)	(0.00995)	(0.00991)
Social Responsibility	0.0124	0.0123	0.0119
	(0.00971)	(0.00970)	(0.00968)
Social Responsibility + Link	0.00840	0.00855	0.00902
	(0.00995)	(0.00995)	(0.00995)
Congratulations	-0.00920	-0.00882	-0.00844
	(0.00964)	(0.00963)	(0.00958)
Outcome mean (control)	0.235	0.235	0.235
Observations	39,548	39,548	39,548
Stratum FE	Yes	Yes	Yes
Week FE	No	Yes	Yes
Controls (LASSO)	No	No	Yes

Notes: This table shows treatment effects of behavioral messages in a sample of 8,019 on-time borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The dependent variable is a dummy equal to one if the borrower is late on any product in the week. In Panel A, the variable of interest is a dummy equal to one if the borrower was assigned to receive any of the message streams. In Panel B, the outcomes of interest are dummies indicating the message stream to which the borrower was assigned. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. In column (3), we use PDS Lasso to select covariates (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

APPENDIX
(for online publication)

Appendix A Stratification Details

We computed quintiles according to the Bank's internal credit score distribution which reflects the probability that a late client meets their repayment obligations in the next month. This probability is calculated with a machine-learning algorithm that takes into account both the historical and the recent repayment behavior of the client. Regarding the segment variable, the Bank classifies clients into different segments that dictate the type of relationship it maintains with the customer. This classification, though not directly related to repayment outcomes, covers different socioeconomic characteristics of the borrower. A different segment results in a different type of customer service, which in turn can affect the client's perception of the bank.

From each stratum in the population of late clients, customers were randomly selected and sent to the strata of the experimental sample, so that the proportion of each stratum in the sample corresponds to the proportion in the population. Then, within each stratum in the sample, clients were randomly assigned to either the control group or one of the six treatment groups. The bank performed this process several times until the final sample fulfilled the balance tests made by the research team.

Appendix B Additional Tables and Figures

Table A1: The Effect of Behavioral Messages, Days Past Due

	Days Past Due		
	A. Pooled Treatments		
	(1)	(2)	(3)
Any message	-0.554*	-0.555*	-0.567*
	(0.313)	(0.313)	-0.312
Outcome mean (control)	6.43	6.43	6.43
Observations	34,781	34,781	34,781
	B. Separate Treatments		
Contract Reminder	-0.639	-0.640	-0.630
	(0.393)	(0.393)	(0.391)
Reciprocity	-0.601	-0.601	-0.611
	(0.403)	(0.403)	(0.400)
Moral Norms	-0.653	-0.652	-0.664*
	(0.401)	(0.401)	(0.399)
Social Norms	-0.921**	-0.922**	-0.991**
	(0.396)	(0.396)	(0.394)
Social Responsibility	-0.141	-0.145	-0.133
	(0.408)	(0.408)	(0.406)
Social Responsibility + Link	-0.368	-0.368	-0.375
	(0.436)	(0.436)	(0.434)
Outcome mean (control)	6.43	6.43	6.43
Observations	34,781	34,781	28,937
Stratum FE	Yes	Yes	Yes
Week FE	No	Yes	Yes
Controls (LASSO)	No	No	Yes

Notes: This table shows treatment effects of behavioral messages in a sample of 7,029 late borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The dependent variable is the number of days past due at the end of the week. For borrowers with multiple products, we take the maximum number of days past due at the end of the week across products. In Panel A, the variable of interest is a dummy equal to one if the borrower was assigned to receive any of the message streams. In Panel B, the outcomes of interest are dummies indicating the message stream to which the borrower was assigned. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. In column (3), we use PDS Lasso to select covariates (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table A2: Differences Across Treatment Effects, p-values

	Contract Reminder	Recipro.	Moral Norms	Social Norms	Social R.	Social R. + link
Contract Reminder		0.6724	0.4882	0.0812	0.8316	0.6986
Reciprocity	0.6724		0.7847	0.1830	0.5241	0.9758
Moral Norms	0.4882	0.7847		0.2894	0.3639	0.7643
Social Norms	0.0812	0.1830	0.2894		0.0502	0.1792
Social R.	0.8316	0.5241	0.3639	0.0502		0.5497
Social R. + Link	0.6986	0.9758	0.7643	0.1792	0.5497	

Notes: This table presents p-values of tests that compare the effect of each individual message on the probability of being late in a given week, as reported in Column (3), Panel B, Table 2. For each comparison, we report the p-value of a test where the null hypothesis is that the effect of the message listed on the line is equal to the effect of the message listed in the column.

Table A3: The Effect of Behavioral Messages, Additional Controls

	Days Past Due			
	A. Pooled Treatments			
	(1)	(2)	(3)	(4)
Any message	-0.0227**	-0.0228**	-0.0221**	-0.0244**
	(0.0112)	(0.0112)	(0.0112)	(0.0114)
Outcome mean (control)	0.593	0.593	0.593	0.591
Observations	34,781	34,781	34,781	33,686
	B. Separate Treatments			
Contract Reminder	-0.0158	-0.0158	-0.0148	-0.0171
	(0.0146)	(0.0146)	(0.0145)	(0.0148)
Reciprocity	-0.0215	-0.0215	-0.021	-0.0257*
	(0.0145)	(0.0145)	(0.0144)	(0.0147)
Moral Norms	-0.0253*	-0.0253*	-0.0248*	-0.0245*
	(0.0145)	(0.0145)	(0.0144)	(0.0147)
Social Norms	-0.0389***	-0.0389***	-0.0398***	-0.0439***
	(0.0146)	(0.0146)	(0.0145)	(0.0148)
Social Responsibility	-0.0128	-0.0131	-0.0115	-0.0118
	(0.0146)	(0.0146)	(0.0145)	(0.0147)
Social Responsibility (Link)	-0.0218	-0.0219	-0.0205	-0.0227
	(0.0146)	(0.0146)	(0.0146)	(0.0149)
Outcome mean (control)	0.593	0.593	0.593	0.591
Observations	34,781	34,781	34,781	33,686
Stratum FE	Yes	Yes	Yes	Yes
Week FE	No	Yes	Yes	No
Controls (LASSO)	No	No	Yes	Yes
Region-week FE	No	No	No	Yes

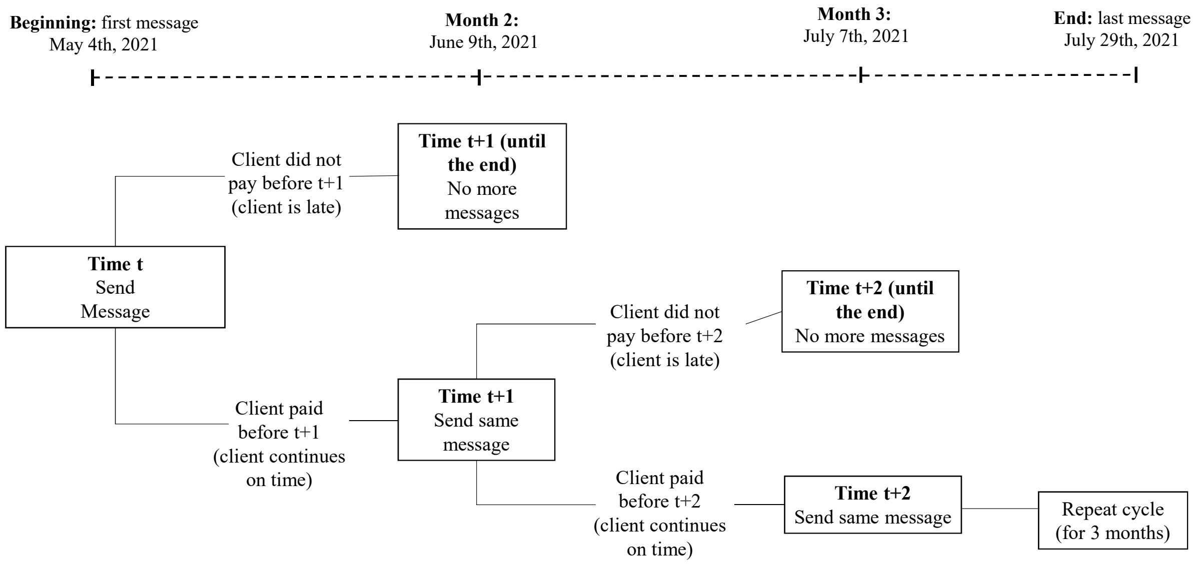
Notes: This table shows treatment effects of behavioral messages in a sample of 7,029 late borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The dependent variable is a dummy equal to one if the borrower is late on any product in the week. In Panel A, the variable of interest is a dummy equal to one if the borrower was assigned to receive any of the message streams. In Panel B, the outcomes of interest are dummies indicating the message stream to which the borrower was assigned. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. All columns include as an additional control the number of days past due of the borrower at the beginning of the intervention. All columns include week fixed effects except for column (4) that includes week fixed effects interacted with region fixed effects. In columns (3) and (4), we use PDS Lasso to select covariates (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table A4: The Effect of Behavioral Messages, Cross Section

	Max Days Past Due	
	A. Pooled Treatments	
	(1)	(2)
Any Message	-0.952**	-0.967**
	(0.458)	(0.455)
Outcome mean (control)	12.93	12.93
Observations	7,029	7,029
	B. Separate Treatments	
Contract Reminder	-0.849	-0.825
	(0.599)	(0.596)
Reciprocity	-1.061*	-1.075*
	(0.600)	(0.596)
Moral Norms	-1.196**	-1.210**
	(0.599)	(0.596)
Social Norms	-1.570***	-1.672***
	(0.599)	(0.596)
Social Responsibility	-0.229	-0.212
	(0.600)	(0.596)
Social Responsibility + Link	-0.804	-0.807
	(0.599)	(0.596)
Outcome mean (control)	12.93	12.93
Observations	7,029	7,029
Stratum FE	Yes	Yes
Controls (LASSO)	No	Yes

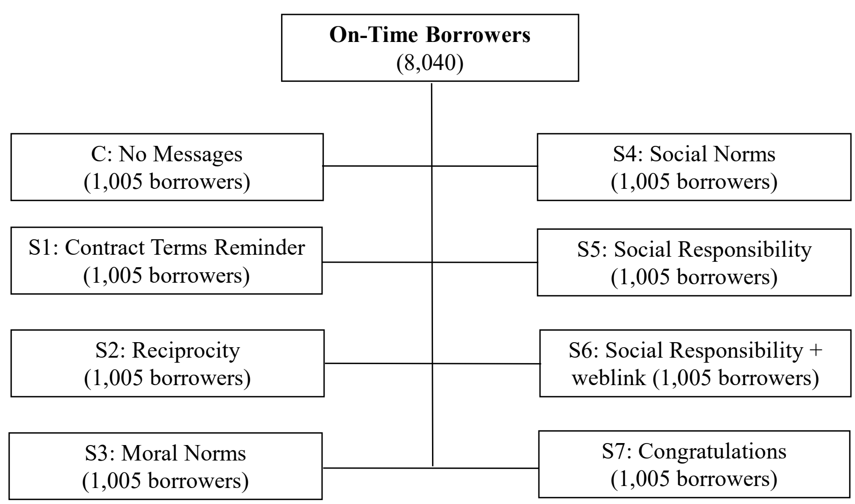
Notes: This table shows treatment effects of behavioral messages in a cross-section of 7,029 late borrowers. The dependent variable is the maximum number of days past due of the borrower (across products) in a five-week time window after the start of the intervention. In Panel A, the variable of interest is a dummy equal to one if the borrower was assigned to receive any of the message streams. In Panel B, the outcomes of interest are dummies indicating the message stream to which the borrower was assigned. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. In column (2), we use PDS Lasso to select covariates (Belloni et al., 2014). Standard errors are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Figure A1: Intervention Timeline, On-time Borrowers



Notes: The figure shows the timeline of our intervention with on-time borrowers. The first text message was pushed to all treated borrowers in the experiment on May 4th, 2021. Borrowers received messages on a monthly basis for 3 months until they became delinquent.

Figure A2: RCT design, On-time Borrowers



Notes: The figure shows the design of our intervention with on-time borrowers. We selected 8,019 late-paying clients and randomly allocated them with equal probability to either the control group or to one of seven different message streams.